Fast Compensation of Current Transformer Saturation

D. Y. Shi, J. Buse, Q. H. Wu, Senior Member, IEEE, L. Jiang

Abstract—This paper presents a novel method for current transformer (CT) saturation detection and compensation. In the method, CT saturation characteristics are represented by a partial nonlinear regression model. The parameters of this model can be estimated rapidly and accurately using both unsaturated and saturated sections of the waveform of a secondary fault current, even in a heavy saturation scenario, where the fault waveform is severely distorted. To reduce the computational load of the estimation, separable nonlinear least squares (SNLLS) method is used to separates the linear and nonlinear parameters of the model, thus reducing the complexity of the estimation. With the fast and accurate parameter estimation, the method can be used for real-time protective relaying. The method has been evaluated on the data obtained from PSCAD/EMTDC simulation. The analysis of the test results shows that the proposed method has superior performance than that offered by conventional compensation algorithms.

Index Terms—Current transformer (CT), saturation, nonlinear regression, separable nonlinear least squares (SNLLS), remanent flux.

I. INTRODUCTION

CURRENT measurements in power systems are usually conducted in iron-core current transformers (CTs), which are reliable devices with acceptable prices. However, the saturation, which may exist in the iron-cores, could distort the secondary currents appearing at the inputs of protection relays [1]. This may lead to malfunction of the protection relays (e.g., under-reach of over-current relays [2], overestimation of fault loop impedance of distance relays [3] and instability of differential relays [4]). To minimize the impact caused by CT saturation, protection relays are designed to either operate with large iron-core CTs, which reduce the probability of the occurrence of CT saturation, or employ algorithms that eliminate the influence of CT saturation. The second method is more economical.

In recent years, various methods have been presented to compensate the distortion of CT secondary currents, as given in [5]–[12]. These methods can be roughly classified into three categories according to how they reconstruct a compensated secondary current from a saturated current:

1) using a complex inverse function to get the compensated current with the saturated current as input [5]–[7];
2) estimating a magnetizing current from the saturated current, and then adding it back to the saturated current to get the compensated current [8]–[10];
3) applying a linear regression on the unsaturated sections of the saturated current to reconstruct the compensated current [11], [12].

The methods of group 1 utilize an artificial neural network (ANN) to form the complex inverse function, which is able to represent the nonlinear magnetizing characteristics of CTs. However, due to the large variations of saturation characteristics from CT to CT, and the steep changes between the input (i.e., saturated secondary currents) and output (i.e., undistorted secondary current) of the function caused by the existence of pre-fault remanent flux in a CT, these ANN based methods are prone to underfitting.

In group 2, the first method presented in [8] estimates the magnetizing current of a saturated CT by applying the calculated instantaneous flux of the CT to the magnetization curve of the CT. This technique performs well, but relies on the assumption that there is no remanent flux in the CT prior to the fault. However the assumption cannot be guaranteed in every fault condition. The other two methods, described in [9], [10], attempt to avoid the remanent flux problem by using difference functions and morphological lifting scheme (MLS), respectively, to detect the exact start points of the distorted secondary currents. The instantaneous flux of a CT at these points is equal to the flux at the knee point in the magnetization curve of the CT. However, the start points detected by these two methods may have large deviations from their true values due to the disturbances caused by anti-aliasing filters and noise.

The methods of group 3, introduced in [11], [12], first utilize wavelet and a group of comparison conditions, respectively, to extract unsaturated sections from a distorted secondary current, and then conduct a linear regression on the extracted sections to estimate the parameters which are used to reconstruct the compensated current. To avoid regression overfitting, the calculation of the regression requires sufficient length of unsaturated sections. Therefore, when the methods are used to deal with a severely saturated current, which has only a very short unsaturation section in each fundamental cycle, more than one cycle of the current is needed to get enough unsaturated sections.

This paper presents a novel method to compensate distorted secondary currents which are caused by CT saturation. To increase compensation speed, both unsaturated and saturated sections of a distorted secondary current are used to conduct a nonlinear regression based on a partial nonlinear regression model, in which linear and nonlinear parameters represent the unsaturated and saturated characteristics of the distorted current respectively. Then a compensated current is reconstructed.
from the parameters estimated by the regression. The remnant flux is considered in the nonlinear part of the model, therefore it do not affect the accuracy of the estimated parameters. Using this method, the accurate parameters can be obtained within a half cycle after fault occurrence. Furthermore, if necessary, the phasor of the secondary current could be directly calculated from the estimated parameters and used in protection relays without reconstructing a compensated current. Usually, the calculation of a multi-dimension nonlinear regression is time-consuming, therefore is difficult to be implemented in a real-time system. However, by exploiting the partial nonlinear characteristic of the model using separable nonlinear least squares (SNLLS) method, the multi-dimension nonlinear regression can be transformed to a combination of a single dimension nonlinear regression and a multi-dimension linear regression. This transformation dramatically reduces the computational load of the regression. It provides the feasibility to implement this compensation method in real-time protective relaying applications.

II. REGRESSION MODEL OF SATURATED SECONDARY CURRENT

An equivalent circuit of a CT is given in Fig. 1, where $Z_m$ is the excitation impedance, $R_s$ and $L_s$ are the total secondary resistance and inductance respectively, $i_p(t)$ is the primary current referred to the secondary side, $i_m(t)$ is the magnetizing current, and $i_s(t)$ is the secondary current. The relationship between $i_p(t)$, $i_m(t)$ and $i_s(t)$ can be described as

$$i_s(t) = i_p(t) - i_m(t). \quad (1)$$

Equation (1), in which $i_s(t)$ is known, can be transformed to a regression model by parameterizing $i_p(t)$ and $i_m(t)$.

A. Parameterization of Primary Current

During the occurrence of a fault, the primary fault current, $i_p(t)$, can be expressed as a superposition of two components, a steady-state sinusoidal waveform (i.e., the phasor of the fault current) and an exponentially decaying DC-offset. The DC-offset is determined by the source voltage, circuit impedance, fault inception angle and X/R ratio of the primary fault path [13]. Then $i_p(t)$ can be represented by

$$i_p(t) = A \cos(\omega t + \theta) + B e^{-\tau t}, \quad (2)$$

where $A$, $\omega$ and $\theta$ are the amplitude, angular speed and inception angle of the sinusoidal waveform respectively, and $B$ and $\tau$ are the initial value and time constant of the exponentially decaying DC-offset respectively. The linear approximation of this equation can be obtained by applying trigonometric expansion and first-order Taylor series expansion on the cosine term and the exponential term of the equation respectively, as given in

$$i_p(t) = -A \sin \theta \sin(\omega t) + A \cos \theta \cos(\omega t) + B - \tau t \quad (3)$$

Then, equation (3) can be parameterized to a linear function, (4), by using unknown parameters, $a_1 \sim a_5$, to replace $-A \sin \theta$, $A \cos \theta$, $B$ and $-\tau$ respectively.

$$i_p(t) = a_1 \sin(\omega t) + a_2 \cos(\omega t) + a_3 + a_4 t \quad (4)$$

B. Parameterization of Magnetizing Current

The magnetizing current, $i_m(t)$, is related to the core flux of the CT through a magnetization curve, which can be converted from the secondary-excitiation curve of the CT provided by CT manufacturers. The magnetization curve also needs to be described in an analytical format before it can be used in a regression model. A high-order power series based model introduced in [14] provides a precise approximation to the magnetization curve. The typical expression of the model is

$$i_m(t) = k_1 \varphi(t) + k_2 \varphi(t)^5 + k_3 \varphi(t)^3 \quad (5)$$

where parameters $k_1 \sim k_3$ represent the magnetizing characteristic of a CT, and $\varphi(t)$ denotes the core flux of the CT. The relationship between the core flux and the secondary current is described in [8], and given by

$$\frac{d\varphi(t)}{dt} = R_s i_s(t) + L_s \frac{di_s(t)}{dt}. \quad (6)$$

Integrating (6) from $t_0$ to $t$ yields

$$\varphi(t) - \varphi(t_0) = R_s \int_{t_0}^{t} i_s(t) dt + L_s (i_s(t) - i_s(t_0)). \quad (7)$$

The $\varphi(t)$ in (5) can be eliminated by substituting it with the $\varphi(t)$ in (7). Since parameters $k_1 \sim k_3$, $R_s$ and $L_s$ in (5) and (7) are known, $i_m(t)$ can be considered as a function, $F_{im}$, which depends on the secondary current $i_s(t)$ from $t_0$ to $t$, and the initial core flux, $\varphi(t_0)$. If $\varphi(t_0)$ is replaced by an unknown parameter $a_5$, $i_m(t)$ can be represented as

$$i_m(t) = F_{im}(i_s(t_0), i_s(t_1) \cdots i_s(t), a_5) \quad (8)$$

where $[i_s(t_0), i_s(t_1) \cdots i_s(t)]$ denotes the samples of secondary current between $t_0$ and $t$.

C. Construction of The Nonlinear Regression Model

A nonlinear regression model can be obtained by applying (4) and (8) to (1):

$$i_a(t) = a_1 \sin(\omega t) + a_2 \cos(\omega t) + a_3 + a_4 t - F_{im}(i_s(t_0), i_s(t_1) \cdots i_s(t), a_5) \quad (9)$$

where parameters, $a_1 \sim a_5$, are unknown; $t$ and $i_a(t)$ are the independent variable and the dependent variable of the regression model, respectively. The objective of the regression analysis based on this model is to estimate $a_1 \sim a_5$ using the sampled $[i_a(t_0), i_a(t_1) \cdots i_a(t)]$. 

Fig. 1. Simplified equivalent circuit of a CT.
III. SEPARABLE NONLINEAR LEAST SQUARES BASED SCHEME

A. Construction of A Nonlinear Least Squares Problem from the Regression Model

Least squares technique is widely used to solve linear and nonlinear regression problems. To apply this technique, the regression model described in (9) needs to be transformed to a least squares problem, whose objective is to find \( x \), the minimizer, for

\[
 r(x) = \sum_{i=0}^{m-1} (f_i(x))^2, \tag{10}
\]

where \( f_i : \mathbb{R}^n \rightarrow \mathbb{R}, i = 0 \cdots m - 1 \) are given regression functions, and \( x \) is a vector of \( n \) unknown parameters. Function \( r(x) \) is the so-called objective function of the least squares problem. \( f_i \) of the regression model constructed in Section II can be formed by shifting all the terms in (9) to the right side of the equation. This gives

\[
 f_i(a) = i_s(t_i) + F_{im}((i_s(t_0) \cdots i_s(t_i)), a_5) - (a_1 \sin(\omega t_i) + a_2 \cos(\omega t_i) + a_3 + a_4 t_i), \tag{11}
\]

where \( a \) is a vector formed with \( a_1 \leq a_5 \), \( t_i = t_0 + i \Delta t \) represents the \( (i+1)^{th} \) sampling time, and \( \Delta t \) is the sampling interval.

Suppose that \( m \) samples of \( i_s(t) \), which may contain samples of unsaturation and saturation sections, are used to conduct the regression analysis. Applying (11) on these samples yields

\[
 f(a) = i_s + F_{im}(a_5) - L a_{(1-4)} \tag{12}
\]

where

\[
 f(a) = \begin{bmatrix} f_0(a) \\ f_1(a) \\ \vdots \\ f_{m-1}(a) \end{bmatrix}, \quad i_s = \begin{bmatrix} i_s(t_0) \\ i_s(t_1) \\ \vdots \\ i_s(t_{m-1}) \end{bmatrix}, \quad a_{(1-4)} = \begin{bmatrix} a_1 \\ a_2 \\ a_3 \\ a_4 \end{bmatrix},
\]

\[
 L = \begin{bmatrix} \sin(\omega t_0) & \cos(\omega t_0) & 1 & t_0 \\ \sin(\omega t_1) & \cos(\omega t_1) & 1 & t_1 \\ \vdots & \vdots & \vdots & \vdots \\ \sin(\omega t_{m-1}) & \cos(\omega t_{m-1}) & 1 & t_{m-1} \end{bmatrix}, \quad \text{and}
\]

\[
 F_{im}(a_5) = \begin{bmatrix} F_{im}([i_s(t_0)], a_5) \\ F_{im}([i_s(t_0), i_s(t_1)], a_5) \\ \vdots \\ F_{im}([i_s(t_0), \cdots i_s(t_i)], a_5) \end{bmatrix}.
\]

Based on (12) and (10), the least squares problem of this regression model can be rewritten in a matrix format

\[
 r_{\text{NLLS}}(a) = f(a)^T f(a). \tag{13}
\]

The values of vector \( a \), which can minimize \( r_{\text{NLLS}}(a) \), is the best estimation for the regression model.

B. Application of Separable Nonlinear Least Squares Method

Various methods have been proposed to solve nonlinear least squares (NLLS) problems [15], [16]. Unlike linear least squares (LLS) problems, which have solutions in analytical form, non-linear problems do not have, and are usually solved by iterative refinement. Usually solving a NLLS problem means a time-consuming process, which is difficult to be applied in a real-time system. The computational load required by solving a NLLS problem mainly depends on the convergent speed and the computational load of each iteration in the solving process.

Through the observation of vector function \( f(a) \) in (12), it can be found that only \( a_5 \) out of the five unknown parameters relates to the nonlinear function, \( F_{im}(a_5) \), and \( a_{(1-4)} \) have linear relationship with \( L \). Based on this characteristic and SNLLS method described in [17], [18], the multi-dimension NLLS problem, \( r_{\text{NLLS}}(a) \), can be split into two least square problems: a one-dimension NLLS problem which only has one unknown parameter, \( a_5 \), and a multi-dimension LLS problem which has four unknown parameters, \( a_{(1-4)} \). The basic concept of the method can be explained clearly by applying the method to the NLLS problem described in (13). First assume that the nonlinear parameter, \( a_5 \), is known, then (13) can be reduced to a linear problem whose close form solution is given by

\[
 a_{(1-4)} = L^+ (i_s + F_{im}(a_5)), \tag{14}
\]

where \( L^+ \) is the Moore-Penrose generalized inverse of \( L \) and can be calculated by

\[
 L^+ = (L^T L)^{-1} L^{top}. \tag{15}
\]

Then a new vector function, which has only one unknown parameter, \( a_5 \), can be obtained by substituting \( a_{(1-4)} \) in (14) back to (12), given by

\[
 f_{\text{SNLLS}}(a_5) = (I - LL^+)(i_s + F_{im}(a_5)) \tag{16}
\]

where \( I \) represents identity matrix. Then the new one-dimension NLLS problem is formed as

\[
 r_{\text{SNLLS}}(a_5) = f_{\text{SNLLS}}(a_5)^T f_{\text{SNLLS}}(a_5). \tag{17}
\]

Once \( a_5 \) is estimated from (17), \( a_{(1-4)} \) can be calculated by applying \( a_5 \) back to (14). Then a healthy secondary current can be reconstructed by applying \( a_{(1-4)} \) back to (4).

The number of dimensions (i.e., parameter set) of the NLLS problem decreases from 5 to 1 by applying SNLLS method. Accordingly convergence speed gets a significant improvement. Furthermore, \( L^+ \) and \( (I - LL^+) \) in (14) and (16) are not related to the sampling data, hence can be calculated off-line which greatly reduces the computational load of each iteration.

Two widely used NLLS solving methods, Levenberg-Marquardt (LM) method [19] and Powell’s Dogleg trust-region method [20], are applied to solve the NLLS problems in (13) and (17). Results have shown that the number of iterations for the two methods is reduced by around 50 percent when SNLLS method is used. Furthermore Dogleg trust-region method generally has better performance than LM method under the same condition.
C. Determination of Initial Points for NLLS Method

With the SNLLS method used in the regression model, it allows the dimension-reduced objective function (i.e., $r_{SNLLS}(a_5)$) to be easily observed and analyzed. The profile of the objective function, upon a group of samples, depends on the existence of CT saturation and the saturation polarity in the samples. The possible shapes of the profile can be divided into three categories: (a) saturation with positive polarity, (b) unsaturation and (c) saturation with negative polarity, as shown in Fig. 2. In both (a) and (c), there is a global minimum which locates between a steep slope and a flat bottom. The relative position among them depends on the polarity of a saturation. The shape in (b) only has a flat bottom, i.e., infinite minima instead of a global minimum.

It is well known that the conventional iterative NLLS solving methods (e.g., LM method, Dogleg method and other Quasi-Newton methods) can only find the local minima of an objective function, and the initial value of the unknown parameters of a NLLS problem is crucial for locating the globe minimum. To guarantee the globe minima of the NLLS problem in (17) could be found, the initial value of $a_5$ is set to be equal to positive and negative maximum possible core flux of the CT for saturations with positive and negative polarities, respectively (i.e., put initial points on the steep slopes beside the global minima in (a) and (c) of Fig. 2). For the unsaturation situation, where every point on the flat bottom is an acceptable solution for $a_5$, the initial value can be set on the slopes of either side of the bottom. Furthermore, the nonlinear regression degrades to a linear regression under this situation. The unknown parameters $a_i$ (1–4) can be directly calculated from (14) by setting $F_{im}(a_5)$ to zero, thus the computational load is greatly reduced.

To determine the existence of CT saturation and the saturation polarity in secondary fault currents, a simple but effective method introduced in [10] is used. This method employs a MLS based detector to extract saturation features from the secondary currents, as shown in Fig. 3. The value of the extracted features is large when CT saturation exists in the secondary currents, and the polarities of the features reflects the polarities of CT saturation.

IV. PERFORMANCE EVALUATION

To evaluate the performance of the proposed method, a wide range of test cases, whose test data are generated form PSCAD/EMTDC, are conducted. These test cases can represent various fault scenarios, thus proof theoretical correctness of the method. The data of the test cases are analyzed using MATLAB. In the following description, all of the quantities are referred to the secondary side.

A sample power system model is established in PSCAD/EMTDC to generate test data for the proposed method. It consists of two sources and a signal transmission line, as shown in Fig. 4. S1 and S2 are equivalent AC voltage sources whose phase-to-phase voltages are $E_{S1} = 220$ kV and $E_{S2} = 220\angle30^\circ$ kV, respectively. $Z_{S1}$ and $Z_{S2}$, whose values are $(2.0 + j7.8542)$, are equivalent impedances of S1 and S2. The total length of the transmission line is chosen to be 300km. A signal phase to ground fault is put on the line. The line parameters, fault locations and fault inception time are adjusted in each test case to generate test data which represent various fault scenarios with different exponentially decaying DC-offsets and different fault current phasors.

Fig. 2. Profiles of $r_{SNLLS}(a_5)$ under different condition. (a) Saturation with positive polarity and no remanent flux. (b) No saturation. (c) Saturation with negative polarity and -80% remanent flux (i.e., the remanent flux is 80% of the flux at the CT saturation point with negative polarity).

Fig. 3. Detection of CT saturation and its polarity. (a) and (c) Negative polarity. (b) and (d) Positive polarity.

Fig. 4. Model of the sample power system.
A CT model with saturation characteristics based on Jiles-Atherton theory described in [21], [22] is employed to generate saturated secondary currents. The CT ratio used in the test cases is 1000/5. The secondary resistance and inductance of the CT are 0.5Ω and 0.8 × 10⁻³H, respectively. The burden of the CT is set to be a pure resistive or 0.5 power factor (pf) burden. The remanent flux is set to vary in a range of -80% to 80% of the saturation flux of the CT.

The performance of the proposed method can be illustrated by the following test cases, which cover several typical fault scenarios and CT secondary parameters. The variations included in the test cases are remanent flux, fault inception angle and secondary burden, whose values are given in Table I.

After each occurrence of fault, a half cycle of the fault data is required to generate accurate compensated secondary current, by using the proposed method.

### A. Simulation Results

A normalized root mean square error (NRMSE), $\varepsilon_{\text{NRMSE}}$, which is defined in (18), is used to measure the compensation accuracy of the test cases in the following sections.

$$
\varepsilon_{\text{NRMSE}}\% = \sqrt{\frac{\sum_{n=1}^{N} (i_p(n) - i_{cs}(n))^2}{\max(i_p) - \min(i_p)}} \times 100,
$$  

(18)

where $i_{cs}$ denotes compensated secondary currents.

1) Case 1

Figure 5 shows the compensated result of case 1. The bold line is the reconstructed secondary current, which is an accurate representation of the primary current. It also shows that the valid output of the method can be obtained within about 10 ms after the fault occurrence. The $\varepsilon_{\text{NRMSE}}$ of this case is 1.36%.

2) Case 2 and Case 3

The remanent flux, which is usually caused by consecutive faults happening on a transmission line, has a great effect on the first half cycle of a secondary fault current. It can increase or reduce the distortion of a saturated secondary current depending on the relative polarity between the DC-offset and the remanent flux of a fault. Figures 6 and 7 show the compensated results of case 2 and case 3, respectively. The distortion of the secondary currents in these two cases is severer than that in case 1 due to the existence of the same polarity 80% and -80% remanent flux, which is the maximum possible remanent flux of a practical CT. The results in the two figures clearly show that the compensated secondary currents are accurately reconstructed without being affected by the big remanent flux. The $\varepsilon_{\text{NRMSE}}$ of these two cases are 1.98% and 1.26%, respectively.

3) Case 4

The secondary burden of a CT, which consists of all the relay impedance and the connecting wire impedance connected to the secondary side of the CT, is another factor closely related to the saturation level of secondary fault currents. Generally, if all the other conditions are kept constant, the larger secondary burden results in severer saturation. The power factor of the secondary burden also affects the shape of the distortion in secondary fault currents. Figure 8 shows the compensated result of case 4. The CT in this case has a 0.5pf secondary burden. As shown in the figure, an accurate compensated current can also be obtained within about 10 ms after the fault occurrence. The $\varepsilon_{\text{NRMSE}}$ of this case is 0.43%.
B. Remarking

1) Computational Load: The computational load of the method and the difference between Dogleg method and LM method are further investigated in case 1, as this case represents the most general scenario and is widely used in comparison. The comparison of the convergence ability between Dogleg method and LM method can be seen in Figures 9 and 10, which provide the value of \( r_{\text{NLLS}} \) and \( r_{\text{SNLLS}} \) at each iteration step of Dogleg method and LM method respectively. Fig. 9 shows the convergence of the NLLS problem defined in (13). It can be seen that the number of iterations required by Dogleg method to obtain an accurate estimation is less than half of that required by LM method. In Fig. 10, which gives the convergence of the SNLLS problem in (17), Dogleg method still has a better performance than LM method. By comparing the convergence speed displayed in these two figures, the number of iterations required by the regression calculation (i.e., LM method and Dogleg method) with SNLLS method is much less than that without SNLLS method. Therefore, the computational load can be greatly reduced by applying SNLLS method.

2) Direct Phasor Measurement: Fundamental amplitude \( A_F \) and relative phase \( \phi \) (i.e., the phase refers to a sine which is 0° at the first sample used to conduct the regression) of the fault current can be directly calculated from the estimated parameters \( a_1 \) and \( a_2 \) by the following two equations respectively:

\[
A_F = \sqrt{a_1^2 + a_2^2} \quad (19)
\]

\[
\phi = \arctan \left( \frac{a_1}{a_2} \right) \quad (20)
\]

These two values can be directly used by over-current relays and distance relays to overcome the disturbance caused by CT saturation and overlapped exponentially decaying DC-offsets. The fundamental amplitude of its primary current and its distorted secondary current can be calculated by full-cycle discrete Fourier transform (FCDFT), as shown in Fig. 11. The fluctuation existing in the fundamental amplitude calculated from the primary current is due to the overlapped DC-offset. The amplitude calculated from the distorted secondary current is seriously corrupted and has a large deviation from the true value. Using (19), the true fundamental amplitude of fault current can be accurately estimated within about 10 ms after the occurrence of the fault, as shown by the bold line in Fig. 11.

V. CONCLUSION AND FUTURE WORK

This paper has proposed a promising method for CT saturation compensation. This method capitalises on the nonlinear regression, NLLS method, and the ability of obtaining fundamental amplitude and relative phase of the secondary fault current directly from the estimated parameters. With these merits, the method obtains accurate parameters faster than the linear regression methods which only use the unsaturated sections, and the computational load of the nonlinear regression is dramatically reduced. The proposed method has been tested with data obtained from simulation, which cover a wide range of fault scenarios. The test results have shown that the method is capable of providing reliable input signals for power

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Fig. 8. Compensated result of case 4.

Fig. 9. Convergence of \( r_{\text{NLLS}} \) with the Dogleg method and the LM method.

Fig. 10. Convergence of \( r_{\text{SNLLS}} \) with the Dogleg method and the LM method.

Fig. 11. Comparison of the values of fundamental amplitude of case 1.
system protection devices. To further evaluate the practical performance of the method, the work of implementing it in a Field Programmable Gate Array (FPGA) based embedded system is in progress.

REFERENCES


D. Y. Shi received his B.Eng. degree in Communication Engineering from Xidian University, China in 2004 and his M.Sc.(Eng) degree in Signal and System form Shenzhen University, China in 2007. He started his Ph.D. study in the Department of Electrical Engineering and Electronics, The University of Liverpool, U.K. from 2007. His research interests include embedded system development and signal processing for power system protection.

J. Buse obtained his B.Eng degree in Electrical Engineering and Electronics from the Department of Electrical Engineering and Electronics, The University of Liverpool, U.K. in July 2006. He started his Ph.D. study in this Department from October 2006. His research interests include embedded systems, multi-agent systems, and their applications in power systems.

Q. H. Wu (M’91, SM’97) obtained an M.Sc.(Eng) degree in Electrical Engineering from Huazhong University of Science and Technology, Wuhan, China, in 1981. From 1981 to 1984, he was appointed Lecturer in Electrical Engineering in the University. He obtained a Ph.D. degree in Electrical Engineering from The Queen’s University of Belfast (QUB), Belfast, U.K. in 1987. He worked as a Research Fellow and subsequently a Senior Research Fellow in QUB from 1987 to 1991. He joined the Department of Mathematical Sciences, Loughborough University, Loughborough, U.K. in 1991, as a Lecturer, subsequently he was appointed Senior Lecturer 1995. In September, 1995, he joined The University of Liverpool, Liverpool, U.K. to take up his appointment to the Chair of Electrical Engineering in the Department of Electrical Engineering and Electronics. Since then, he has been the Head of Intelligence Engineering and Automation Research Group working in the areas of systems control, computational intelligence and electric power and energy. He has authored and coauthored more than 320 technical publications, including 155 journal papers, 20 book chapters and 3 research monographs entitled ‘IP Network-based Multi-agent Systems for Industrial Automation - Information management, condition monitoring and control of power systems’ ‘Protective Relaying of Power Systems Using Mathematical Morphology’ and ‘Condition Monitoring and Assessment of Power Transformers using Computational Intelligence’ published by Springer. Professor Wu is a Chartered Engineer, Fellow of IET and Senior Member of IEEE. His research interests include nonlinear adaptive control, mathematical morphology, evolutionary computation, machine learning and power system control and operation.

L. Jiang (M’00) received the B.Sc. and M.Sc.(Eng.) degrees from Huazhong University of Science and Technology, China, and the Ph.D. degree from the University of Liverpool, Liverpool, U.K., all in electrical engineering, in 1992, 1996 and 2001, respectively. He was a Research Assistant at the University of Liverpool from 2001 to 2003, Research Associate at Department of Automatic Control and Systems, The University of Sheffield, U.K., from 2003 to 2005, and a Senior Lecturer in the Department of Engineering, The University of Glamorgan, U.K., from 2005 to 2007. He has been a Lecturer in Electrical Engineering in The University of Liverpool since September 2007. His research interests include power systems automation and control, induction machine and drives and renewable energy.